

# Examining the synergistic effect of CO<sub>2</sub> emissions on PM<sub>2.5</sub> emissions reduction: Evidence from China

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## ABSTRACT

Under the background of global climate change, China has been confronted with the dual pressure of CO<sub>2</sub> emissions reduction and PM<sub>2.5</sub> pollution control. This research aims to explore the mechanism of changes in PM<sub>2.5</sub> emissions, which are the key airborne pollutants causing haze. Furthermore, it quantifies the impacts of CO<sub>2</sub> emissions reduction activities on PM<sub>2.5</sub> emissions reduction. This study takes aggregate PM<sub>2.5</sub> emissions instead of PM<sub>2.5</sub> concentration index as the research object. Based on an extended kaya identity, LMDI approach is first performed to decompose the changes of PM<sub>2.5</sub> emissions during 1998–2014, taking into consideration the synergistic effect of carbon emissions on PM<sub>2.5</sub> emissions. Furthermore, following LMDI decomposition, this study adopts the econometric methods to quantify the synergistic effect of CO<sub>2</sub> emissions reduction on PM<sub>2.5</sub> emissions reduction over the period 1999–2014. The empirical results are as follows: (1) the LMDI decomposition results specify that the synergistic emissions reduction accounts for the most of the reduction in PM<sub>2.5</sub> emissions. In addition, energy intensity changes also contribute to the reduction in PM<sub>2.5</sub> emissions; (2) by contrast, it is found that the economic development effect is the main factor resulting in the increase of PM<sub>2.5</sub> emissions, while the contributions of the energy emission intensity effect and population effect to PM<sub>2.5</sub> emissions changes are relatively little; (3) all the models show CO<sub>2</sub> emissions reduction activities will significantly contribute to PM<sub>2.5</sub> emissions reduction; (4) for every 10,000 t increase in CO<sub>2</sub> emissions reduction, PM<sub>2.5</sub> emissions reduction will increase by 3.3 t, and the potential for synergistic emissions reduction of PM<sub>2.5</sub> differs distinctly among different provinces; (5) technological progress and population density positively influence PM<sub>2.5</sub> emissions reduction, while coal consumption rate has a negative impact on PM<sub>2.5</sub> emissions reduction, in addition, there is an inverted U-shaped curve relationship between per capita GDP and PM<sub>2.5</sub> emissions reduction.

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## 1. Introduction

With the acceleration of industrialization and urbanization in China, the issue of air pollution has become increasingly serious. Specially, haze pollution has frequently occurred in recent years, and the airborne PM<sub>2.5</sub> particulates not only lead to environmental health damage, but also cause many negative impacts on economic development, including affecting foreign investment, introduction of talented people and tourism development. PM<sub>2.5</sub> has become the primary pollutant worsening the quality of China's atmospheric

environment, and it has the characteristics of wide range of influence, high frequency of occurrence, and difficulty in tackling. To address the increasingly prominent haze pollution, it is necessary to scrupulously and comprehensively investigate the internal changing mechanism of haze pollution in China, so as to provide a scientific basis for the formulation of haze mitigation policies.

Air pollution and climate change are two challenges faced by the atmospheric environment today. Developed countries have basically completed air pollution control at the end of the 20th century, and climate change issues have begun to arouse the global attention in the early 21st century (Dong et al., 2019b; Li and Su, 2017). At present, developed countries mainly bear the international responsibility for greenhouse gas emissions reduction (Li et al., 2019). As a developing country, China is still in the period of industrialization. Due to long-term extensive economic development, China is faced with not only the domestic pressure of air pollution control,

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but also the international pressure of carbon emissions reduction (Xian et al., 2018). In 2007, China surpassed the United States and became the largest carbon emitter in the world (Dong et al., 2018a). Accordingly, China has made lots of efforts in carbon emissions reduction, and made many emissions reduction commitments. For example, the carbon intensity in 2020 is expected to be decreased by 40%–45% compared with the 2005 level (Dong et al., 2018b), and the carbon intensity in 2030 will be lower than that in 2005 by 60%–65% (Dong et al., 2018c). The emissions of greenhouse gas and atmospheric pollutants are homologous, and both of them are mainly caused by the combustion of fossil fuels. The reductions of CO<sub>2</sub> and PM<sub>2.5</sub> emissions are consistent in action, and the realization of collaborative control over atmospheric pollutants and greenhouse gas emissions has a realistic basis. Air quality can be effectively improved in the process of reducing greenhouse gas emissions, and the resulting environmental health gain will reduce the cost of emissions reduction and increase the cost efficiency of emissions reduction technologies (Yang et al., 2013). If China's carbon emissions reduction targets can be achieved, the haze pollution will be alleviated to some extent. In 2015, the revised law on the prevention and control of atmospheric pollution (NPC, 2015), known as the “most stringent law on prevention and control of atmospheric pollution in the history of China”, first proposed “collaborative control of atmospheric pollutants and greenhouse gas emissions”. The work plan for the control of greenhouse gas emissions during the 13th Five-Year Plan period and the 13th Five-Year Plan for the protection of ecological environment (State Council of China, 2016a, 2016b) have clearly identified “strengthening the collaborative control of air pollutant emissions and carbon emissions” as an important means of low-carbon transformation. As China's economy enters a new normal, the quality of ecological environment has become an important indicator for the performance appraisal of local government officials. For China, which is in a critical period of economic transformation, the collaborative control of carbon emissions and air pollution is an important policy path. There are still many challenges in how to achieve collaborative control of air pollution and carbon emissions, which deserve our in-depth study.

In response to carbon emissions, the Chinese government has not only made a series of emissions reduction commitments, but also formulated a number of specific measures, including orders and control measures, and carbon emissions trading (Dong et al., 2019a), with some remarkable results achieved. The governmental measures for haze mitigation are introduced late in China. In 2012, the Ministry of Environmental Protection in China passed the Ambient Air Quality Standards (DEP, 2012), and began to carry out monitors on haze pollution in various places. The Action Plan for Air Pollution Prevention and Control (State Council of China, 2013) clearly proposed 35 specific haze control measures, and set clear air pollution control target for each region. For instance, the PM<sub>2.5</sub> concentration in the Beijing-Tianjin-Hebei region, Yangtze River Delta and Pearl River Delta should be reduced by 25%, 20% and 15%, respectively. As the research on haze pollution has started late in China, compared with carbon emissions reduction, the haze pollution control policy is still not mature, and the understanding of the socio-economic factors of haze pollution is still insufficient. At present, most regions in China have still not achieved effective PM<sub>2.5</sub> control, meanwhile, the regional haze pollution dominated by industrial source emissions is still serious. The quantitative study on the impact of carbon emissions reduction activities on PM<sub>2.5</sub> emissions reduction is helpful in formulating practical emissions mitigation measures for policy makers.

Synergistic emissions reduction includes two aspects: one is the co-benefits of carbon emissions reduction caused by pollutant emissions reduction, and the other is the co-benefits of pollutant

emissions reduction caused by carbon emissions reduction, which is the focus of this study. As China's carbon emissions regulation tightens and the carbon emissions trading mechanism becomes more mature, enterprises are faced with tremendous pressure from the increase in the cost of carbon emissions reduction. The pressure can be partly relieved through the incentive mechanism under which carbon emissions reduction activities bring about pollutant emissions reduction. The quantitative analysis of the impacts of carbon emissions reduction activities on PM<sub>2.5</sub> emissions reduction has important reference value for policy makers, which can encourage enterprises to achieve carbon emissions reduction targets, help reduce PM<sub>2.5</sub> emissions, and ultimately achieve a win-win situation of economic growth and environmental improvement. Based on the actual conditions of China, it is of great significance to explore the synergistic effect of CO<sub>2</sub> reduction activities on PM<sub>2.5</sub> emissions reduction.

This paper is intended to resolve the following three questions. What factors have led to changes in China's PM<sub>2.5</sub> emissions? How much reduction in PM<sub>2.5</sub> emissions will result from the reduction in per unit CO<sub>2</sub>? Are there differences in synergistic emissions reduction in different areas? This paper focuses on the co-benefits of PM<sub>2.5</sub> emissions reduction caused by carbon emissions reduction. Firstly, the synergistic effect of carbon emissions is introduced into the Kaya identity of PM<sub>2.5</sub> emissions, and the influencing factors of PM<sub>2.5</sub> emissions changes are studied by LMDI decomposition method. Then, the econometric analysis is applied to quantify the impacts of CO<sub>2</sub> emissions reduction activities on PM<sub>2.5</sub> emissions reduction, specifically, the estimation methods used in this paper include Fixed Effect estimation (FE), Feasible Generalized Least Squares (FGLS), comprehensive FGLS, and Generalized Method of Moments (GMM) estimation for the robustness test.

The remainder of this paper is arranged as follows. Section 2 presents a brief review of the related studies. Section 3 provides the methodology and data. Section 4 presents and discusses the results of LMDI decomposition. Section 5 shows the results and corresponding discussion of econometric model. The final section concludes this research and provides some policy implications.

## 2. Literature review

Scholars have conducted a lot of studies on the factors affecting PM<sub>2.5</sub>, and found that PM<sub>2.5</sub> is mainly affected by meteorological conditions and human activities. Although the frequent occurrence of haze pollution is affected by climatic factors to some extent, it is ultimately caused by extensive economic development, industrial structure imbalance, low energy efficiency and inefficient environmental governance (Shao et al., 2016). Therefore, the socio-economic factors affecting haze pollution have attracted more attention. The existing studies regarding the influencing factors of haze pollution mainly adopt econometric analysis methods (Ji et al., 2018; Lin et al., 2013). Based on the STIRPAT model, Xu and Lin (2016) analyze the effects of economic development, urbanization, private car ownership, coal consumption and energy efficiency on China's PM<sub>2.5</sub> emissions in 2001–2012, and find there are distinct differences in the impacts of various factors among different regions. At present, the research on haze pollution mainly adopts the concentration index due to the lack of aggregate PM<sub>2.5</sub> emissions data. Therefore, the decomposition analysis method is rarely found in PM<sub>2.5</sub> related studies. For instance, Guan et al. (2014) employ the Structural Decomposition Analysis (SDA) to study the socio-economic drivers of PM<sub>2.5</sub> emissions changes in China from 1997 to 2010, and find that efficiency gains can offset emissions growth caused by economic growth and other factors. In addition, capital formation is the most important factor for PM<sub>2.5</sub> emissions in the final demand side, but the resulting emissions is

declining, and export is the only positive driver in the final demand side. In the studies with respect to air pollution control, the Computable General Equilibrium (CGE) model has been widely utilized, the commonly used policy tools include resource tax (Sancho, 2010), sulfur tax (Xu and Masui, 2009), and carbon tax (Allan et al., 2014). Wei and Ma (2015) combine the haze control policies (including sulfur tax and carbon tax) with energy mix adjustment and technological progress, and adopt CGE model to conduct scenario analysis, the results show that energy mix optimization and technological progress are the fundamental means to alleviate haze pollution. However, the CGE model focuses on simulating the implementation effect of the expected policy combination, and it is difficult to simultaneously examine the mechanism of the effects of multiple factors on haze pollution. In addition, the CGE model has difficulty in capturing the dynamic changes of policy effects over time.

Synergistic effect was first proposed by the Intergovernmental Panel on Climate Change (IPCC) in 2001, and the IPCC defined the synergistic effect as other socio-economic benefits (in addition to climate improvements) brought about by policy actions to achieve greenhouse gas emissions mitigation. Subsequently, the Organization for Economic Cooperation and Development (OECD), the US Environmental Protection Agency, and the European Environment Agency define the synergistic effect from different perspectives. In fact, the source of synergistic effect is not limited to energy conservation policies, greenhouse gas emissions reduction policies, or air pollution control policies. Synergistic effect has attracted more and more attention from scholars in the field of environmental research. Xue et al. (2015) utilize the life cycle analysis method to quantitatively evaluate the co-benefits of wind power generation. They find that, compared with coal-fired power plants, wind power plants emit lower carbon dioxide by 97.48%, and discharge lower atmospheric pollutants  $\text{SO}_2$ ,  $\text{NO}_x$  and  $\text{PM}_{10}$  by 80.38%, 57.31% and 30.91%, respectively. The similar findings are found by the study of Ma et al. (2013) on wind power in Xinjiang. Hasanbeigi et al. (2013) analyze the synergistic effect caused by the energy-saving policies of the cement sector in Shandong province, including the reductions in  $\text{PM}_{10}$  and  $\text{SO}_2$  emissions, and find the resulting health benefits reduce the costs of energy saving.

The synergistic effect of greenhouse gas emissions reduction on air pollution mitigation has been confirmed by a large number of studies. Wagner and Amann (2009) employ the GAINS model to evaluate the implementation effect of greenhouse gas emissions reduction measures in Annex I of the Kyoto Protocol, and conclude that the  $\text{CO}_2$  emissions reduction target can be achieved with an additional 5% reduction in  $\text{SO}_2$ ,  $\text{NO}_x$ , and PM emissions. Vennemo et al. (2009) investigate the benefits and costs of three different  $\text{CO}_2$  mitigation strategies (including intensity control, total emissions control, and sectoral intensity control), and conclude that intensity control has the greatest environmental co-benefits for China, while it has a negative impact on rural residents. Shrestha and Pradhan (2010) adopt the bottom-up minimum cost optimization energy system model to study the synergistic effect of Thailand's carbon emissions reduction policies. It is concluded that under the 30% carbon reduction target,  $\text{SO}_2$  will be reduced by 43%, what's more, the constraints of carbon emissions reduction targets are conducive to promoting the optimization and upgrading of energy mix. Many studies suggest that greenhouse gas emissions reduction strategies will lead to improvement in air pollution and resulting public health benefits (Groosman et al., 2011; Haines et al., 2009; Nemet et al., 2010), specially, this kind of synergistic effect can work out to the largest extent in developing countries (Nemet et al., 2010). He et al. (2010) simulate the synergistic effects under different combined scenarios of energy policies (greenhouse gases or air pollutants oriented), including greenhouse gas

emissions reduction, air pollutant mitigation and health benefits. The existing literature about the collaborative management of air pollutants and greenhouse gas emissions mostly employs complex model to conduct simulation analysis considering a single policy or a combination of multiple emissions reduction measures. However, there are too many assumptions and the quantitative results can only be regarded as predictions or theoretical values, without the retrospective analysis of historical data. Based on historical data of  $\text{CO}_2$  and  $\text{PM}_{2.5}$  emissions, this paper utilizes the combination of index decomposition analysis and econometric analysis methods to study the changing mechanism of  $\text{PM}_{2.5}$  emissions, and quantify the impacts of  $\text{CO}_2$  reduction activities on  $\text{PM}_{2.5}$  emissions reduction.

Through the review of the existing literature, we find the following deficiencies. First, with regard to the research on the influencing factors of haze pollution,  $\text{PM}_{2.5}$  or  $\text{PM}_{10}$  concentration index is commonly used rather than aggregate emissions index, moreover, the decomposition analysis method is rarely adopted to study the changes in  $\text{PM}_{2.5}$  emissions. Second, the existing literature has not taken into consideration the synergistic effect of  $\text{CO}_2$  emissions reduction on  $\text{PM}_{2.5}$  emissions reduction. China is faced with the dual pressure of  $\text{CO}_2$  and  $\text{PM}_{2.5}$  emissions reductions. It is necessary to quantify the impacts of  $\text{CO}_2$  emissions reduction activities on  $\text{PM}_{2.5}$  emissions reduction from a macro policy level, thereby providing a scientific basis for enterprises and policy makers to formulate emissions reduction strategies. Third, when it comes to haze pollution related studies, few research has combined the decomposition analysis with the econometric analysis. This paper takes advantages of the two methods to analyze the driving factors of  $\text{PM}_{2.5}$  emissions and the ways to promote synergistic emissions reduction of  $\text{PM}_{2.5}$ . The above-mentioned deficiencies motivate this research. Apart from previous studies, this study contributes to the existing literature in the following ways. (1) This paper solves the problem that provincial  $\text{PM}_{2.5}$  emissions data are not available, and incorporates the synergistic effect of carbon emissions into the Kaya identity of  $\text{PM}_{2.5}$  emissions. Accordingly, the LMDI method is utilized to decompose  $\text{PM}_{2.5}$  emissions changes into the synergistic effect of carbon emissions, energy emission intensity effect, energy intensity effect, economic development effect and population effect. (2) Based on LMDI decomposition results, the econometric analysis method is employed to quantitatively analyze the impact of carbon emissions reduction activities on  $\text{PM}_{2.5}$  emissions reduction, and examine whether the synergistic emissions reduction is affected by energy mix and technological progress. (3) This paper employs several rigorous econometric techniques to estimate the static panel data model, including FE, FGLS and comprehensive FGLS estimations. Furthermore, the GMM estimation is performed to conduct robustness test given possible endogeneity problems. All models prove the existence of synergistic  $\text{PM}_{2.5}$  emissions reduction resulting from  $\text{CO}_2$  emissions reduction. (4) In addition to the synergistic effect of  $\text{CO}_2$  emissions reduction on  $\text{PM}_{2.5}$  emissions reduction, this paper also takes into consideration such socio-economic variables as energy mix, technological progress, per capita GDP and population density. A comprehensive empirical identification of the influencing factors of  $\text{PM}_{2.5}$  emissions reduction reveals that there is a significant inverted U-shaped relationship between per capita GDP and  $\text{PM}_{2.5}$  emissions reduction. (5) In view of considerable heterogeneity among different regions, this paper divides China's 30 provinces into three major economic regions: the western, central and eastern regions. Accordingly, the application of LMDI is to investigate  $\text{PM}_{2.5}$  emissions changes at total economy, regions and provinces levels. In addition, we also compare the potential synergistic emissions reduction of  $\text{PM}_{2.5}$  in 30 provinces.

### 3. Methodology and data

#### 3.1. LMDI decomposition

The logarithmic mean divisia index (LMDI) method is first proposed by Ang et al. (1998). As an important branch of index decomposition analysis (IDA), this approach can address zero values and does not contain residuals in its decomposition results, which is widely utilized in energy-related research. This paper employs the LMDI method to analyze the influencing factors of PM<sub>2.5</sub> emissions changes in China.

The nationwide PM<sub>2.5</sub> emissions can be expressed as:

$$\begin{aligned} PM &= \sum_i PM_i = \sum_i \frac{PM_i}{C_i} \cdot \frac{C_i}{E_i} \cdot \frac{E_i}{GDP_i} \cdot \frac{GDP_i}{P_i} \cdot P_i \\ &= \sum_i PMOC_i \cdot EM_i \cdot EI_i \cdot GPC_i \cdot P_i \end{aligned} \quad (1)$$

where  $i$  denotes the  $i$ th region,  $PM_i$  is PM<sub>2.5</sub> emissions,  $C_i$  represents CO<sub>2</sub> emissions,  $E_i$ ,  $GDP_i$  and  $P_i$  represent energy consumption, GDP and population size, respectively;  $PMOC$  is the PM<sub>2.5</sub> emissions per unit of CO<sub>2</sub> emissions, i.e., the quantitative measurement of synergistic emissions reduction, which is the focus of this paper. In addition,  $EM$ ,  $EI$ ,  $GPC$  denote energy emission intensity (i.e., energy mix), energy intensity and GDP per capita.

Let  $\Delta PM$  refer to the variation in PM<sub>2.5</sub> emissions from year 0 (the base period) to year  $t$ , which can be decomposed by LMDI approach into the following effects:

$$\begin{aligned} \Delta PM &= PM^t - PM^0 = \sum_i PMOC_{it} \cdot EM_{it} \cdot EI_{it} \cdot GPC_{it} \cdot P_{it} - \\ &\sum_i PMOC_{i0} \cdot EM_{i0} \cdot EI_{i0} \cdot GPC_{i0} \cdot P_{i0} = \Delta PM_{PMOC} + \Delta PM_{EM} + \Delta PM_{EI} + \Delta PM_{GPC} + \Delta PM_P \end{aligned} \quad (2)$$

The five effects can be deduced as:

$$\Delta PM_{PMOC} = \sum_i \frac{PM_i^t - PM_i^0}{\ln PM_i^t - \ln PM_i^0} \ln \frac{PMOC_i^t}{PMOC_i^0} \quad (3)$$

$$\Delta PM_{EM} = \sum_i \frac{PM_i^t - PM_i^0}{\ln PM_i^t - \ln PM_i^0} \ln \frac{EM_i^t}{EM_i^0} \quad (4)$$

$$\Delta PM_{EI} = \sum_i \frac{PM_i^t - PM_i^0}{\ln PM_i^t - \ln PM_i^0} \ln \frac{EI_i^t}{EI_i^0} \quad (5)$$

$$\Delta PM_{GPC} = \sum_i \frac{PM_i^t - PM_i^0}{\ln PM_i^t - \ln PM_i^0} \ln \frac{GPC_i^t}{GPC_i^0} \quad (6)$$

$$\Delta PM_P = \sum_i \frac{PM_i^t - PM_i^0}{\ln PM_i^t - \ln PM_i^0} \ln \frac{P_i^t}{P_i^0} \quad (7)$$

Consequently, the change in PM<sub>2.5</sub> emissions from the base period to target period can be decomposed into the contributions of five driving factors.  $\Delta PM_{PMOC}$  is the synergistic effect of carbon emissions, which reflects the impact of energy-related carbon emissions activities on PM<sub>2.5</sub> emissions.  $\Delta PM_{EM}$  is the energy emission intensity effect, reflecting the impact of energy mix

changes on PM<sub>2.5</sub> emissions.  $\Delta PM_{EI}$  is the energy intensity effect, which reflects the impact of energy efficiency changes on PM<sub>2.5</sub> emissions.  $\Delta PM_{GPC}$  is the economic development effect, and  $\Delta PM_P$  is the population effect in the model.

#### 3.2. Econometric model

In the previous section, we make the appropriate transformation on the basic model of Kaya identity (Kaya, 1990), and take into account the synergistic effect of carbon emissions on PM<sub>2.5</sub> emissions, thereby providing a theoretical basis for empirical analysis. Based on the previous factor decomposition process, this paper adds into the econometric model various variables representing the synergistic effect of carbon emissions, energy emission intensity effect, energy intensity effect, economic development effect and population effect, respectively (i.e., CO<sub>2</sub> emissions reduction, energy mix, technological progress, per capita GDP, population density). In addition, in order to examine the existence of the Environmental Kuznets Curve (EKC) hypothesis, the quadratic term of GDP per capita is introduced into the model. Finally, a two-way fixed effects model is established in the following form:

$$\begin{aligned} PMR_{it} &= \beta_0 + \beta_1 CR_{it} + \beta_2 EM_{it} + \beta_3 TP_{it} + \beta_4 GPC_{it} + \beta_5 GPC2_{it} \\ &\quad + \beta_6 PD_{it} + \gamma_t + \delta_i + \varepsilon_{it} \end{aligned} \quad (8)$$

where  $i$  indicates the  $i$ th province,  $t$  is time;  $PMR$  indicates PM<sub>2.5</sub>

emissions reduction,  $CR$ ,  $EM$ ,  $TP$ ,  $GPC$ , and  $PD$  serve as the proxy variables for the five decomposed effects through LMDI decomposition.  $CR$  indicates CO<sub>2</sub> emissions reduction,  $\beta_1$  is the estimated coefficient of  $CR$ , which represents the quantitative measurement of synergistic emissions reduction and is the key observation indicator in this paper.  $GPC$  refers to GDP per capita, indicating the economic development level and residents' income levels, and  $GPC2$  is the quadratic term of  $GPC$ .  $EM$  and  $PD$  represent energy mix and population density, respectively. As the proxy variable of the energy intensity effect,  $TP$  indicates technological progress given two main reasons. First, if energy intensity is included as an independent variable directly, Eq. (8) may have serious multicollinearity. Second, there is evidence that technological progress is the main factor leading to the decline of China's energy intensity (Garbaccio et al., 1999). As a result, technological progress is utilized to characterize the impact of energy efficiency on PM<sub>2.5</sub> emissions reduction.  $\delta_i$  is the non-observed effect in each province that does not change over time, which specifies persistent differences among provinces, such as consumption habits, natural resources endowments and environmental regulations. The time-fixed effect is considered in the model as well, and  $\gamma_t$  indicates the time non-observed effect. Considering the limitation of sample observation, the degree of freedom will be largely lost and the variance of the estimated parameter will increase if introducing (T-1) time dummy variables. Therefore, in order to save parameters in the model, this paper introduces the time trend item to control the effects of time-

varying factors such as energy prices, energy and environment related policies.  $\varepsilon_{it}$  is a random error term irrelevant to time and region.

### 3.3. Variable description and data source

In this study, we focus on two main environmental issues in China, i.e., carbon emissions and PM<sub>2.5</sub> emissions. Since there is no officially published provincial carbon emissions data, this paper calculates the CO<sub>2</sub> emissions of 30 provinces in China from 1998 to 2014 using the data of such three energy sources as coal, petroleum and natural gas by multiplying their carbon emission coefficients, as shown in Eq. (9). Carbon emission coefficients and conversion factors from physical units to coal equivalent are derived from IPCC (2006), Xu et al. (2006), and Hu and Huang (2008).

$$C_{it} = \sum_j E_{itj} \cdot \mu_j \quad (9)$$

In Eq. (9),  $C_{it}$  is the CO<sub>2</sub> emissions of province  $i$  in year  $t$ ,  $E_{itj}$  indicates the  $j$ th energy consumption (expressed in standard coal equivalent),  $\mu_j$  is the corresponding carbon emission coefficient. Total coal includes raw coal, cleaned coal, briquette, coke, etc. Total petroleum products contain crude oil, gasoline, kerosene, diesel, etc.

The PM<sub>2.5</sub> emissions data are obtained from the Surface Process Analysis and Simulation Laboratory of Peking University (Huang et al., 2014). Specifically, the data for 30 provinces are extracted from the monthly average grids (1998–2014) through ArcGIS software, then, we get annual-average PM<sub>2.5</sub> emissions for each province. The data are calculated according to the method proposed by Huang et al. (2014), and PM<sub>2.5</sub> emissions mainly originate from combustion and industrial process sources. The trend of PM<sub>2.5</sub> emissions (in 10,000 t) in 1998, 2006 and 2014 are shown in Figs. 1–3. On the whole, haze pollution was concentrated in the economically developed and densely populated North China region. In addition, the PM<sub>2.5</sub> emissions in the eastern region were relatively larger than those in the central and western regions.

In the LMDI decomposition, the sample interval covers 1998–2014. Energy consumption data come from the China Energy Statistical Yearbook (NBSC, 2015a), and the population and GDP

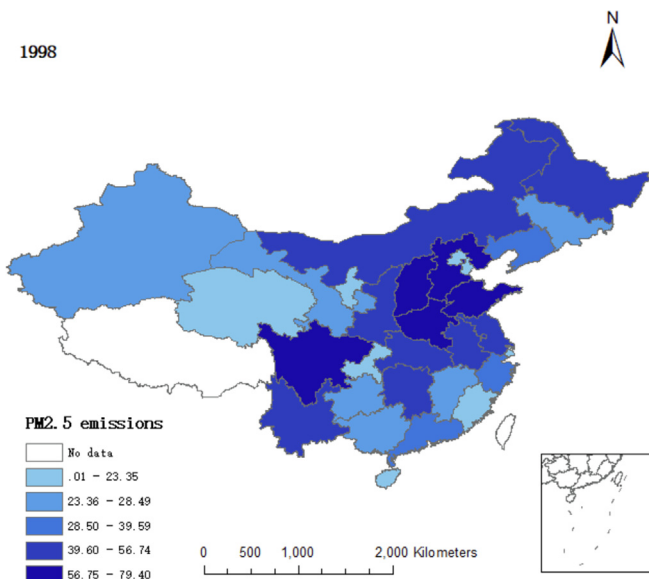


Fig. 1. Spatial distribution of PM<sub>2.5</sub> emissions in 1998 (10,000 t).

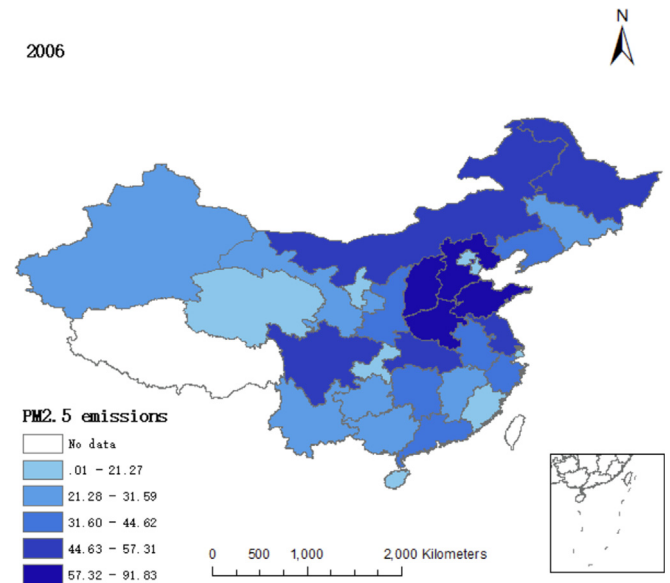


Fig. 2. Spatial distribution of PM<sub>2.5</sub> emissions in 2006 (10,000 t).

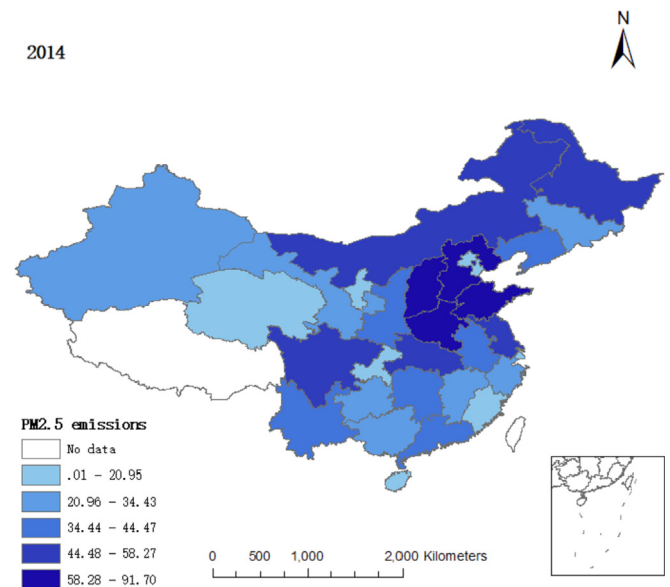


Fig. 3. Spatial distribution of PM<sub>2.5</sub> emissions in 2014 (10,000 t).

data come from the China Statistical Yearbook (NBSC, 2015b). In order to eliminate the impact of price fluctuation, GDP and per capita GDP are converted into 2000 constant prices through the deflators.

In the econometric analysis section, this paper utilizes the panel data of 30 provinces from 1999 to 2014, and the summary of variables is shown in Table 1. CO<sub>2</sub> emissions reduction (CR), energy mix (EM), technological progress (TP), GDP per capita (GPC) and population density (PD) are adopted to represent the synergistic effect of carbon emissions, energy emission intensity effect, energy intensity effect, economic development effect and population effect, respectively. In particular, since the original data are used for empirical analysis, variable unit adjustments (see Table 1) are needed to avoid the occurrence of outliers in the estimated coefficients which may result in the difficult explanation for results. The data of energy mix come from China Energy Statistical

**Table 1**  
Summary of variables.

Variables	Definition	Unit of measurement	Data source
PMR	PM <sub>2.5</sub> emissions reduction	Thousand tons	Huang et al. (2014)
CR	CO <sub>2</sub> emissions reduction	Ten thousand tons	China Energy Statistical Yearbook (NBSC, 2015a), IPCC (2006), Xu et al. (2006), Hu and Huang (2008)
EM	Share of coal consumption in total energy consumption	Percent	China Energy Statistical Yearbook (NBSC, 2015a)
TP	Number of patent applications granted	Ten thousand pieces	China Statistical Yearbook (NBSC, 2015b)
GPC	GDP per capita	Thousand yuan per capita (at 2000 constant prices)	China Statistical Yearbook (NBSC, 2015b)
PD	The ratio of total population to total area	Person per square kilometers	China City Statistical Yearbook (NBSC, 2015c)

Yearbook (NBSC, 2015a), the data of technological progress and GDP per capita are derived from China Statistical Yearbook (NBSC, 2015b), and data on population density are from China City Statistical Yearbook (NBSC, 2015c). As for the explained variable, i.e. PM<sub>2.5</sub> emissions reduction  $PMR_{it}$ , based on the study of Fu and Yuan (2017) on SO<sub>2</sub> emissions reduction in China's power industry, the PM<sub>2.5</sub> emissions reduction of province  $i$  in year  $t$  is defined as:

$$PMR_{it} = PM_{i,t-1} - PM_{it} \quad (10)$$

The core explanatory variable, i.e. CO<sub>2</sub> emissions reduction  $CR_{it}$ , is calculated as follows:

$$CR_{it} = C_{i,t-1} - C_{it} \quad (11)$$

In Eq. (11),  $CR_{it}$  is the CO<sub>2</sub> emissions reduction of province  $i$  in year  $t$ .

#### 4. Results and discussion of LMDI decomposition

##### 4.1. Decomposition results of the whole economy

The additive decomposition is utilized to study the influencing factors of PM<sub>2.5</sub> emissions in China from 1998 to 2014, the decomposition results are shown in Fig. 4. Total effect denotes China's PM<sub>2.5</sub> emissions increment compared with last year, and other values in Fig. 4 are the contributions of five factors to the changes in PM<sub>2.5</sub> emissions. For the total economy, PM<sub>2.5</sub> emissions decline during the period from 1998 to 2002, rise during 2002–2007, and go down and up over the period 2007–2014. It can be seen from Fig. 4 that the increase of PM<sub>2.5</sub> emissions is mainly caused by economic development. The average annual contribution of the economic development effect during 1998–2014 reaches 1,036,700 t. By contrast, the reduction in PM<sub>2.5</sub> emissions is mainly affected by the synergistic effect of carbon emissions, which has huge potential for synergistic emissions reduction of PM<sub>2.5</sub>. The average annual contribution of the synergistic effect of carbon emissions during 1998–2014 reaches –758,700 t, which indicates that reducing the PM<sub>2.5</sub> emissions per unit of CO<sub>2</sub> emissions is an effective way to reduce PM<sub>2.5</sub> emissions, and the potential for the collaborative reductions of CO<sub>2</sub> and PM<sub>2.5</sub> emissions should be vigorously explored. It is found that the effect of energy intensity is positive during 2001–2002 and 2003–2005, but negative in other periods. On the whole, the changes in energy intensity lead to the decrease in PM<sub>2.5</sub> emissions, with average annual contribution of –317,800 t, which indicates the energy efficiency improvements can significantly reduce PM<sub>2.5</sub> emissions. The changes in PM<sub>2.5</sub> emissions caused by the energy emission intensity effect during 1998–2014 is either positive or negative, with average annual contribution of –26,300 t, indicating that the energy emission intensity has a weak negative impact on PM<sub>2.5</sub> emissions. Due to the characteristics of being “rich in coal, lack of oil and less gas”, China's resource endowment has limited space for energy mix adjustment,

but its emissions reduction potential cannot be ignored. The PM<sub>2.5</sub> changes caused by the population effect are mostly positive except for the period of 2004–2005, with annual average contribution of 68,300 t, indicating that the population changes will promote the increase of PM<sub>2.5</sub> emissions. To be specific, the expansion of the population will inevitably lead to a series of production activities and increase the energy demand, thereby increasing pressure on the environment and resulting in an increase in PM<sub>2.5</sub> emissions.

On the whole, the economic development effect, energy intensity effect and synergistic effect of carbon emissions significantly influence PM<sub>2.5</sub> emissions, while the effects of population and energy emission intensity are relatively weak. During the period from 1998 to 2014, the impact of energy emission intensity is either positive or negative, economic development and population contribute to increasing PM<sub>2.5</sub> emissions, while the energy intensity effect and synergistic effect of carbon emissions are conducive to reducing PM<sub>2.5</sub> emissions. Specially, enhancing the synergistic effect of carbon emissions (i.e., promoting the collaborative reductions of CO<sub>2</sub> and PM<sub>2.5</sub> emissions) is the most effective way to reduce PM<sub>2.5</sub> emissions.

##### 4.2. Decomposition results of three economic regions

As shown in Figs. 1–3, China displays considerable heterogeneity in PM<sub>2.5</sub> emissions among different regions, which deserves our research attention. In this section, based on the traditional division of Chinese economic regions as well as industrial development and geographical proximity, we divide China's 30 provinces into three major economic regions<sup>1</sup> (Xie et al., 2018), i.e., Eastern China, Central China and Western China, and explore the regional differences in PM<sub>2.5</sub> changes during 1998–2014 in each region. The decomposition results are shown in Fig. 5. The total effect indicates the variation in PM<sub>2.5</sub> emissions from 1998 to 2014, and it can be seen that PM<sub>2.5</sub> emissions present faint changes in three regions. As shown in Fig. 5, the economic development effect is still the most important factor for the increase of PM<sub>2.5</sub> emissions in three regions. The synergistic effect of carbon emissions and the energy intensity effect are still the main reasons for the decline in PM<sub>2.5</sub> emissions. The changes in population promote the increase of PM<sub>2.5</sub> emissions, but the effect in the eastern, central and western regions is distinctly different. The contribution of the population effect in Eastern China reaches 777,200 t, much higher than the 109,200 t in Central China and 119,500 t in Western China. The eastern region is the most economically developed in China, where the population size has exploded with the rapid growth of the economy. Thus, the

<sup>1</sup> Eastern region includes Beijing, Shanghai, Tianjin, Fujian, Hebei, Liaoning, Jiangsu, Shandong, Hainan, Zhejiang, Guangdong. Central region comprises Henan, Shanxi, Hubei, Jilin, Heilongjiang, Anhui, Hunan, Jiangxi. Western region contains Inner Mongolia, Sichuan, Chongqing, Xinjiang, Shaanxi, Gansu, Guizhou, Yunnan, Guangxi, Qinghai, Ningxia.

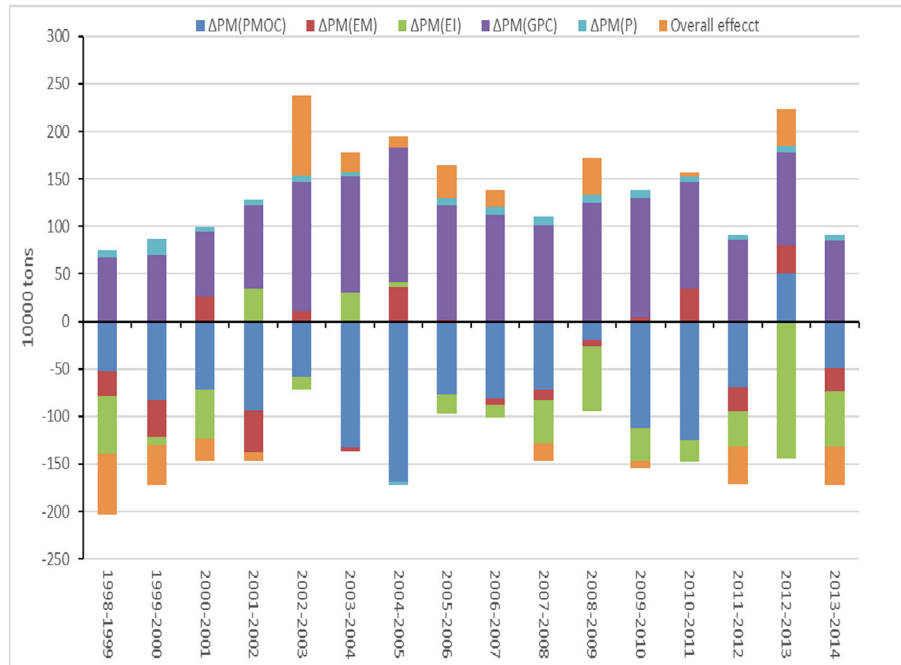


Fig. 4. Decomposition results of PM<sub>2.5</sub> emissions changes in China.

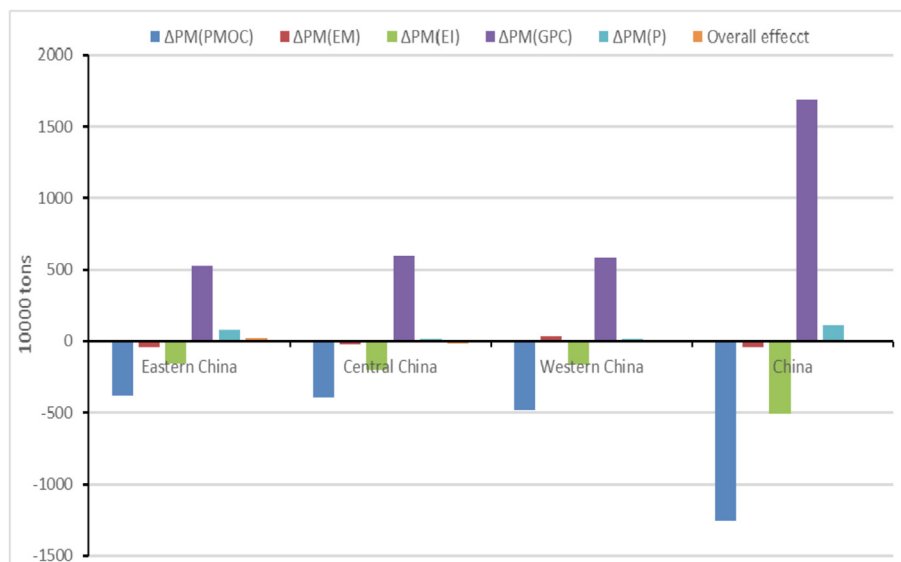


Fig. 5. Decomposition results of PM<sub>2.5</sub> emissions changes in three regions.

population effect in the eastern region is significantly greater than that in the central and western regions. In Western China, the energy emission intensity effect results in an increase in PM<sub>2.5</sub> emissions. In Central and Eastern China, it has a negative impact on PM<sub>2.5</sub> emissions, indicating that energy mix in the central and eastern regions shows a low-carbon clean trend and the PM<sub>2.5</sub> emissions can be reduced to some extent through the optimization of energy mix, while energy mix in western region has not been effectively improved. At the nationwide level, the changes in energy emission intensity lead to a slight reduction in PM<sub>2.5</sub> emissions, and the impacts of other factors on PM<sub>2.5</sub> emissions are consistent with the regional decomposition results.

On the whole, the contribution value of each factor to PM<sub>2.5</sub> emissions differs significantly among three economic regions. The

synergistic effect of carbon emissions and energy intensity effect are factors promoting the reduction of PM<sub>2.5</sub> emissions. The economic development effect and population effect are the reasons for the increase in PM<sub>2.5</sub> emissions. Specially, the energy emission intensity in Western China leads to an increase in PM<sub>2.5</sub> emissions, indicating that the energy mix in Western China is urgent to be improved.

#### 4.3. Decomposition results of 30 provinces

Fig. 6 shows the decomposition results of PM<sub>2.5</sub> emission changes in China's 30 provinces. The total effect denotes the variation in PM<sub>2.5</sub> emissions from 1998 to 2014 in each province. It can be seen that the changes in PM<sub>2.5</sub> emissions in various provinces

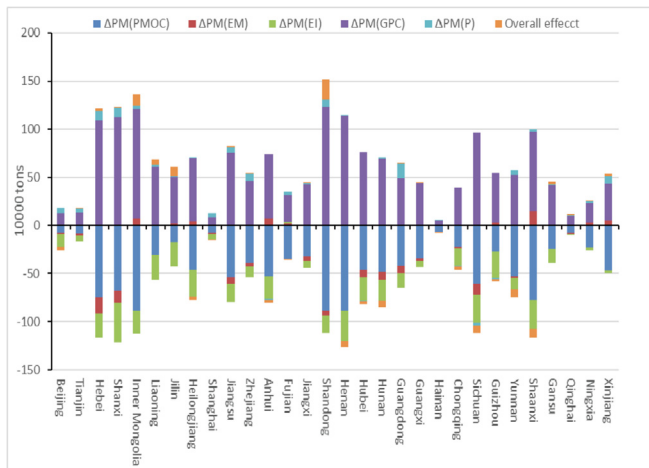


Fig. 6. Decomposition results of PM<sub>2.5</sub> emissions changes in 30 provinces.

are quite different. The PM<sub>2.5</sub> emissions in 16 provinces, including Hebei, Inner Mongolia, Shandong, etc, increase during 1998–2014, among which Shandong province presents the largest increment of 200,600 t. On the contrary, PM<sub>2.5</sub> emissions in other 14 provinces decrease, specially, Yunnan province shows the largest decline of 85,500 t.

Among the five effects, the synergistic effect of carbon emissions contributes the most to decreasing PM<sub>2.5</sub> emissions in all provinces, indicating that the implementation of carbon emissions reduction policies has effectively promoted the synergistic emissions reduction of PM<sub>2.5</sub>. However, the co-benefits of PM<sub>2.5</sub> emissions reduction are largely different among 30 provinces. The five provinces with the largest absolute values of contributions are Henan, Shandong, Inner Mongolia, Shaanxi and Hebei. The provinces with the largest and smallest absolute values are Henan (888,900 t) and Hainan (63,400 t), respectively, indicating that there are huge differences in the potential for synergistic emissions reduction of PM<sub>2.5</sub> among provinces, which is due to considerable regional disparities of socioeconomic development in China.

Fig. 6 shows energy intensity changes contribute to reducing PM<sub>2.5</sub> emissions in most province except Fujian province with contribution value of 15,700 t. This is because the increase in energy intensity in Fujian leads to a slight increase in PM<sub>2.5</sub> emissions. However, in most provinces, the energy intensity effect leads to the reduction in PM<sub>2.5</sub> emissions, indicating that these provinces have achieved remarkable results in reducing energy intensity and improving energy efficiency. The contribution of the energy intensity effect is significantly different in different provinces. The provinces with the largest and smallest absolute values are Shanxi (−410,900 t) and Hainan (−1,700 t), respectively. As a traditional coal-producing province, Shanxi's economic development has been relying on coal consumption for a long time, resulting in serious resource and environmental problems. The energy intensity in Shanxi drops from 4.11 t of coal equivalent per 10,000 yuan in 2007 to 2.36 t of coal equivalent per 10,000 yuan in 2014. Shanxi has significantly reduced the energy consumption per unit of GDP by improving the energy efficiency and developing low energy-consuming industries, thereby effectively promoting the reduction of PM<sub>2.5</sub> emissions.

The effect of economic development is positive in all provinces. It should be noted that the economic development effect is the main driving force for the increase of PM<sub>2.5</sub> emissions, which shows that China's provinces develop their economies at the expense of the environmental deterioration and public health loss, and they are still in the stage of extensive economic development.

Furthermore, there are huge differences in the contributions of the economic development effect among provinces. The provinces with the largest and smallest contributions are Shandong (1,229,300 t) and Hainan (48,100 t), respectively. China is in the critical period of economic transformation, promoting the collaborative management of CO<sub>2</sub> and PM<sub>2.5</sub> emissions is an important way to curb environmental issues.

Among the five effects, the energy emission intensity effect has relatively little impact on PM<sub>2.5</sub> emissions. The effect of energy emission intensity in such 20 provinces as Hebei, Shanxi, Sichuan, etc, is negative, and the accumulated effect is up to −1,013,500 t, indicating that the transformation into the low-carbon clean energy mix in these provinces has effectively promoted the reduction of PM<sub>2.5</sub> emissions. The effect of energy emission intensity in other 10 provinces is positive because these provinces have long relied on traditional fossil energy consumption and have not effectively improved their energy mix.

In most provinces, the effect of population is positive. However, only five provinces such as Anhui, Hubei, Chongqing, Sichuan and Guizhou present weak negative effects. The main reason is that these provinces are known for their large labor outputs in consideration of population migration, therefore, the changes in population contribute to decreasing PM<sub>2.5</sub> emissions.

On the whole, for all provinces, economic development is estimated to be the most important factor contributing to the increase of PM<sub>2.5</sub> emissions, while the synergistic effect of carbon emissions is the largest contributor to the drop of PM<sub>2.5</sub> emissions. Strengthening the synergistic effect of carbon emissions is the most effective way to reduce PM<sub>2.5</sub> emissions. In addition, it is important to reduce energy intensity and improve energy efficiency, thereby reducing PM<sub>2.5</sub> emissions. The population effect causes slight increase in PM<sub>2.5</sub> emissions in most provinces, which indicates its impact on PM<sub>2.5</sub> emissions is limited. In most provinces, the contribution of energy emission intensity is negative. Although energy emission intensity effect contributes little to PM<sub>2.5</sub> emissions changes in most provinces, its potential influence on PM<sub>2.5</sub> emissions reduction is great for the whole country. For most provinces, there is still large space for the optimization of energy consumption structure, and it is of great significance to reduce coal consumption and increase utilization of quality and cleaner energy, thereby effectively reducing PM<sub>2.5</sub> emissions.

## 5. Results and discussion of econometric model

### 5.1. Panel unit root test and co-integration test

The application of LMDI is to investigate the contributions of the synergistic effect of carbon emissions, energy emission intensity effect, energy intensity effect, economic development effect and population effect to PM<sub>2.5</sub> emissions changes during 1998–2014 at total economy, regions and provinces levels. In addition to the changing mechanism of PM<sub>2.5</sub> emissions, an understanding of the channels through which each factor affects PM<sub>2.5</sub> emissions is useful when making specific emissions reduction measures. Based on the results obtained by LMDI decomposition, this paper adopts econometric analysis methods to study the impacts of proxy variables (i.e., CO<sub>2</sub> emissions reduction, energy mix, technological progress, per capita GDP and population density) on PM<sub>2.5</sub> emissions reduction, using the historical data of CO<sub>2</sub> and PM<sub>2.5</sub> emissions during 1999–2014. More importantly, this paper focuses on quantifying the synergistic effect of CO<sub>2</sub> emissions reduction activities on PM<sub>2.5</sub> emissions reduction. Generally speaking, most economic variables are non-stationary sequences. In order to avoid spurious regression, it is necessary to test the stability of variable sequences before the regression analysis, that is, whether there is a

**Table 2**  
Results of panel unit root tests.

	Series	Fisher ADF		Fisher PP		LLC	
		constant	Trend and intercept	constant	Trend and intercept	constant	Trend and intercept
Levels	PMR	−2.7503	1.0468	38.1443***	35.4452***	−8.3050***	−8.8124***
	CR	4.7708***	3.1674***	18.8407***	15.3854***	−7.1415***	−10.1597***
	EM	1.7657**	4.9579***	2.7139***	9.4018***	−2.3376***	−5.0459***
	TP	−2.2016	5.2633***	−4.8685	−3.9649	4.9814	−3.8802***
	GPC	1.3177*	11.1270***	−3.8037	1.6822**	1.1666	−4.6839***
	PD	−0.2808	11.9281***	23.2684***	34.7018***	−7.2329***	−7.5807***
First difference	PMR	2.3603***	2.2548**	122.9618***	135.2901***	−22.1514***	−30.4643***
	CR	1.8191**	10.4396***	83.5477***	91.8090***	−20.7025***	−23.1599***
	EM	3.6326***	16.5003***	70.7638***	69.7636***	−12.2646***	−24.0260***
	TP	8.9224***	36.4778***	6.3209***	5.2060***	−2.8647***	−2.4822***
	GPC	5.1944***	9.5448***	25.9438***	28.0357***	−8.5161***	−13.7832***
	PD	6.8390***	12.1078***	111.8903***	103.4200***	−11.3041***	−25.6590***

Note: \*\*\*p < 0.01, \*\*p < 0.05, \*p < 0.1; the number of lags of the series is chosen according to the Akaike information criterion (AIC).

unit root. The unit root test for the panel data needs to consider the heterogeneity of cross-section sequences, and the panel unit root test consists of two major categories. The one assumes that each cross-section sequence has the same unit root, including LLC test, Breitung test and Hadri test. The other assumes that different cross-section sequences have different unit roots, such as IPS test, Fisher-ADF test and Fisher-PP test. In this paper, the commonly used LLC, Fisher-ADF and Fisher-PP tests are utilized to perform panel unit root tests. The possible cross-section correlation is alleviated, and the results of panel unit root tests are presented in Table 2. It is shown that some variables are non-stationary, but their first difference series significantly reject the null hypothesis of containing the unit root. On the whole, all the test results are combined to determine that every variable is a first-difference stationary sequence. Furthermore, it is necessary to examine whether there exists any co-integration relationship between PMR and the independent variables. The Kao co-integration test yields an ADF statistic of −11.7147, which rejects the null hypothesis that there is no

significant co-integration relationship between the explanatory variables and PMR at confidence level of 1%. In addition, considering that there may exist multi-collinearity between explanatory variables, this paper utilizes VIF statistic to test whether there is multi-collinearity in the model. The test results show that the VIF values of all variables are less than 2, indicating there is no multi-collinearity problem in the data set.

## 5.2. Results and discussion

This paper establishes a two-way fixed effects model considering time fixed effect and individual fixed effect, and adopts several methods to estimate the model, including Fixed Effect estimation (FE), FGLS (only considering the intra-group autocorrelation) and CFGLS (considering both intra-group autocorrelation, inter-group heteroscedasticity and cross-sectional correlation), among which the CFGLS estimation results are more effective. Table 3 presents the regression results obtained by various

**Table 3**  
Estimates results through different estimation methods.

Variables	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)
	FE	FE	FGLS	CFGLS	CFGLS	CFGLS	CFGLS
CR	0.0037*** (0.0008)	0.0037*** (0.0008)	0.0037*** (0.0013)	0.0033*** (0.0003)	0.0033*** (0.0003)	0.0005 (0.0010)	0.0036*** (0.0004)
EM	−0.1041 (0.1325)	−0.1806 (0.1517)	−0.1834 (0.1870)	−0.1776** (0.0776)	−0.1363*** (0.0504)	−0.2631*** (0.0748)	−0.1703** (0.0767)
TP	0.4956# (0.3050)	0.5825** (0.2705)	0.5855 (0.6121)	0.7554** (0.3165)	0.2594 (0.4591)	1.1234** (0.5317)	−0.3772 (0.3827)
GPC	0.5019# (0.3031)	1.8877** (0.8126)	1.8891* (0.9790)	1.9101*** (0.5837)	1.1802** (0.5937)	1.7302** (0.7338)	2.8683*** (0.8009)
GPC2		−0.0175* (0.0086)	−0.0175* (0.0095)	−0.0142* (0.0086)	−0.0128 (0.0094)	−0.0202* (0.0108)	−0.0275*** (0.0106)
Eastern*CR					−0.0014*** (0.0005)		
Central*CR					0.0018*** (0.0005)		
EM*CR						0.0000** (0.0000)	
TP*CR							−0.0002*** (0.0001)
PD	0.0308 (0.0257)	0.0464 (0.0358)	0.0459* (0.0235)	0.0429** (0.0218)	0.0281 (0.0489)	0.0932*** (0.0294)	0.0345 (0.0414)
T	−1.2702** (0.5865)	−2.3399*** (0.8423)	−2.3431** (1.0271)	−2.2184*** (0.4940)	−1.6082*** (0.5975)	−1.9235*** (0.5980)	−3.0931*** (0.7164)
Constant	1.2946 (13.6704)	−6.9258 (16.3388)	−50.4177* (27.8036)	8.0823 (24.1401)	14.1354 (23.9543)	10.3895 (24.3771)	5.9582 (23.7614)
Observations	480	480	480	480	480	480	480
Provincial fixed effects	✓	✓	✓	✓	✓	✓	✓
Time fixed effects	✓	✓	✓	✓	✓	✓	✓

Note: Robust standard errors in parentheses, \*\*\*p < 0.01, \*\*p < 0.05, \*p < 0.1, #p < 0.15.

estimation methods, and all models demonstrate the existence of synergistic PM<sub>2.5</sub> emissions reduction caused by carbon emissions reduction. As shown in Table 3, as a baseline reference, Model (1) is the regression result based on FE estimation without the quadratic term of GPC. Models (2)–(4) report the estimation results through FE, FGLS and CFGLS, respectively. Models (5)–(7) give the estimation results through CFGLS with the interaction terms of CR. It can be seen that the estimated coefficients in Model (4) are more significant than Model (2) and Model (3). Since the CFGLS estimation is highly effective and can resolve the autocorrelation and heteroscedasticity problems, the following discussion is mainly based on the results of Model (4).

The results show that the estimated coefficient of the core explanatory variable CR is 0.0033 and significant at the 1% level, which indicates that the CO<sub>2</sub> emissions reduction activities will significantly affect PM<sub>2.5</sub> emissions reduction. This means for every 10,000 t increase in CO<sub>2</sub> emissions reduction, PM<sub>2.5</sub> emissions reduction will increase by 3.3 t, confirming the feasibility of collaborative reductions of CO<sub>2</sub> and PM<sub>2.5</sub> emissions. China is currently in the stage of industrialization and faced with the dual pressure of carbon emissions and haze pollution, the ecological environment predicament needs to be resolved. China has formulated a number of specific policies on carbon emissions reduction, and made a series of emissions reduction commitments to the international community. However, the mitigation policy for haze pollution is still insufficient. The quantitative analysis on the impacts of carbon emissions reduction activities on PM<sub>2.5</sub> emissions reduction can provide important information for policy makers.

Among the control variables, the coefficient of energy mix is significantly negative at the 5% level, indicating that the proportion of coal consumption hinders the reduction in PM<sub>2.5</sub> emissions. Coal contains a large amount of nitrogen and sulfur, and its combustion will produce the main ingredients of PM<sub>2.5</sub>, i.e. sulfur dioxide and nitrogen oxides. The coefficient of technological progress is positive and significant at the 5% level. Technological progress will enhance the energy efficiency, in addition, the substitution of new power generation technology for coal-fired power generation makes great potential for reductions in sulfur, nitrogen and carbon, thereby leading to PM<sub>2.5</sub> emissions reduction. The coefficient of population density is significantly positive, which indicates population density contributes to promoting PM<sub>2.5</sub> emissions reduction. This is because population agglomeration can promote intensive energy utilization and improve the energy utilization efficiency, thereby

reducing PM<sub>2.5</sub> emissions. As shown in Table 3, the coefficient of per capita GDP is significantly positive, and the coefficient of its quadratic term is significantly negative, indicating that there is a nonlinear inverted U-shaped relationship between per capita GDP and PM<sub>2.5</sub> emissions reduction. In the early stage of economic development, economic growth contributes to promoting PM<sub>2.5</sub> emissions reduction. As the economy develops to a certain level, PM<sub>2.5</sub> emissions reduction potential becomes smaller and emissions reduction decreases accordingly.

We estimate the potential synergistic emissions reduction of PM<sub>2.5</sub> using historical CO<sub>2</sub> emissions reduction by multiplying the coefficient of CR 0.0033 obtained in Model (4), and the annual average during the observation period (1999–2014) is taken. Since CO<sub>2</sub> emissions in all provinces increase during the observation period (i.e., the annual average historical CO<sub>2</sub> emissions reduction are negative), this paper defines the absolute value of synergistic emissions reduction of PM<sub>2.5</sub>  $|\beta_1 \cdot \Delta CR|$  as the potential synergistic emissions reduction of PM<sub>2.5</sub> in each province. Fig. 7 shows the potential synergistic emissions reduction of PM<sub>2.5</sub>. Since we have made some adjustments to variables units in econometric analysis (see Table 1), the unit of emissions reduction is kiloton in Fig. 7. It can be seen that there are huge differences in the potential synergistic emissions reduction of PM<sub>2.5</sub> in different provinces. In particular, in Inner Mongolia and Shandong, the increase in PM<sub>2.5</sub> emissions indirectly caused by the increase in CO<sub>2</sub> emissions is more than 13,000 t, while the least is reported in Hainan, Beijing and Qinghai. Comparing the potential synergistic PM<sub>2.5</sub> emissions reduction and historical PM<sub>2.5</sub> emissions reduction, Zhejiang has a potential synergistic emissions reduction 28 times higher than the historical emissions reduction. Guangdong has a potential synergistic emissions reduction 22 times higher than the historical emissions reduction. Shanxi has a potential synergistic emissions reduction 19 times higher than the historical emissions reduction. By contrast, the gaps in other provinces are relatively smaller.

In order to study whether there is any difference in the synergistic effect of CO<sub>2</sub> emissions reduction on PM<sub>2.5</sub> emissions reduction among the eastern, central and western regions, this paper adds the interaction terms between regional dummy variables and CR in Model (5). The results show that the synergistic effect in the central region is significantly larger than that in the western and eastern regions. According to the estimation results of Model (4), the economically developed eastern region has crossed the inflection point of the inverted U-shaped curve between economic

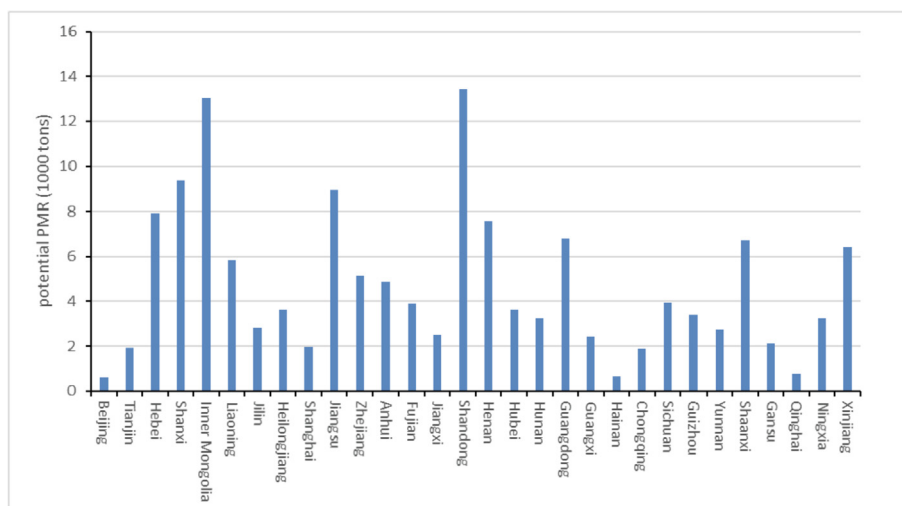


Fig. 7. Potential synergistic emissions reduction of PM<sub>2.5</sub>.

**Table 4**  
Results of robustness tests.

Variables	Model (8)	Model (9)	Model (10)
	LSDV	GMM	GMM
CR	0.0037*** (0.0008)	0.0071*** (0.0025)	0.0072** (0.0028)
EM	−0.1806 (0.1566)		−0.0826 (0.1997)
TP	0.5825** (0.2792)		0.2297 (0.6493)
GPC	1.8877** (0.8388)		2.0830* (1.1616)
GPC2	−0.0175* (0.0088)		−0.0217** (0.0103)
PD	0.0464 (0.0369)		0.0559 (0.0427)
T	−2.3399** (0.8694)	0.0526 (0.3139)	−2.0407# (1.2782)
Observations	480	450	450
Provincial fixed effects	✓	✓	✓
Time fixed effects	✓	✓	✓
Underidentification test (Kleibergen-Paap rk LM statistic)		28.416***	23.790***
Weak identification test (Cragg-Donald Wald F statistic/Kleibergen-Paap rk Wald F statistic)		49.497/27.610	36.862/23.185
Endogeneity test		2.070	1.919
Hansen J statistic		Exactly identified	Exactly identified

Note: Robust standard errors in parentheses; \*\*\*p < 0.01, \*\*p < 0.05, \*p < 0.1, #p < 0.15.

development and PM<sub>2.5</sub> emissions reduction. Compared with central and western regions, PM<sub>2.5</sub> emissions in eastern region are less sensitive to CO<sub>2</sub> emissions reduction. For some developed provinces in eastern region, pollutant emissions have become the rigid need to stabilize local economic development, which partly offsets the negative impacts of carbon emissions reduction activities to some extent. In Model (6) and Model (7), the interaction terms between energy mix, technological progress and CR are introduced to study the expansion mechanism of synergistic effect. As shown in Model (4) and Model (6), after controlling the interaction term between energy mix and CR, the coefficient of CR decreases and is no longer significant, the negative impact of energy mix increases, and the coefficient of interaction term approaches to zero. Although the energy mix has a direct negative impact on PM<sub>2.5</sub> emissions reduction, it is not ideal to promote the synergistic effect by improving energy mix. Therefore, in order to enhance synergistic emissions reduction of PM<sub>2.5</sub>, in addition to reducing the proportion of coal consumption, it is crucial to improve the efficiency of energy processing conversion and utilization in CO<sub>2</sub> emissions reduction activities, such as promoting the clean utilization of fossil energy especially coal and improving the cleanliness of the production process, thereby strengthening synergistic emissions reduction of PM<sub>2.5</sub>. According to Model (4) and Model (7), after controlling the interaction term between the technological progress and CR, the coefficient of CR slightly increases, the coefficient of technological progress is no longer significant, and the coefficient of the interaction term is significantly negative, indicating that technological progress will weaken the synergistic effect. At present, the control of CO<sub>2</sub> emissions mainly depends on energy-saving measures. There is no feasible end-of-pipe control technology for CO<sub>2</sub> emissions reduction. For example, carbon capture and storage (CCS) may increase electricity consumption and lead to more pollutant emissions due to higher power consumption, therefore, there should be a trade-off between reducing greenhouse gas emissions and local air pollutants (Yang et al., 2013). Although technological progress (or energy efficiency improvement) contributes to mitigating CO<sub>2</sub> emissions to a certain extent, it should be noted that as the energy utilization efficiency increases, the marginal cost of energy services decreases, which may result in the rebound effect of energy resources (Gillingham et al., 2016;

Greening et al., 2000). Thus, energy efficiency improvement may lead to more energy consumption and not be conducive to PM<sub>2.5</sub> emissions reduction.

### 5.3. Robustness test

There are three sources of endogeneity problems: measurement bias, missing variables, and reverse causality, which may reduce the robustness of model and lead to biased estimation results. In order to address possible endogeneity problems, this paper assumes the core explanatory variable CR is an endogenous variable, adopts the lagged term of CR as instrument variable, and estimates the model by Generalized Method of Moments (GMM). Since the results of 2SLS (Two stage least squares) and GMM are exactly the same, the estimation result of 2SLS is not reported in Table 4. The first stage estimation result of 2SLS shows that the lagged term of CR has a good explanatory power for CR (the estimated coefficient is 0.2854, P value is 0.000). As shown in Table 4, the endogenous test shows that CR is not related to the disturbance term and can be considered as an exogenous explanatory variable because the null hypothesis of CR as the exogenous variable cannot be rejected even at the 15% significant level. Since the number of endogenous variables is equal to that of instrument variables, the over-identification test fails in the case of exact identification, and the exogenous nature of the instrument variables can only be qualitatively analyzed. China has made many carbon emissions reduction commitments, including achieving its carbon emissions peak by 2030 and lowering carbon intensity by 40%–45% from the 2005 level by 2020 (Dong et al., 2018c). Under the binding targets of carbon emissions reduction, enterprises will decide on future emissions reduction measures based on historical emissions reduction. Therefore, the previous carbon emissions reduction will affect current PM<sub>2.5</sub> emissions reduction by influencing the current carbon emissions reduction, while the current PM<sub>2.5</sub> emissions reduction has no impact on the previous carbon emissions reduction. Accordingly, the lagged term of CR is selected as the exogenous instrument variable in this paper. The weak instrument variable test (i.e., weak identification test) reports two statistics. The Cragg-Donald statistic is obtained under the assumption of spheroidal disturbance term, and the Kleibergen-Paap statistic relaxes this assumption. For the Model

(9), the Cragg-Donald statistic and the Kleibergen-Paap statistic are much larger than the critical value of 16.38 under the 10% bias, and the similar test result is reported in the Model (10). Thus, weak identification test can reject the null hypothesis of the lagged term of CR as weak instrument variable, and the instrument variable is considered to be strongly related with CR, indicating there is no weak instrument variable problem considering the lagged term of CR as instrument variable.

Table 4 reports the GMM estimation results, and the least square dummy variable (LSDV) estimation results are provided as a baseline reference. In all models, the coefficients of CR are significantly positive, supporting the existence of the synergistic effect of CO<sub>2</sub> emissions reduction on PM<sub>2.5</sub> emissions reduction. In addition, the coefficient signs of the control variables are consistent with the results in Table 3. On the whole, the previous conclusions have been further confirmed. Using the lagged term of CR as instrument variable, ordinary least squares (OLS) estimation is more effective than instrument variable estimation in the absence of endogeneity problems. As shown in Table 4, the standard errors in Model (9) and Model (10) through GMM estimation are higher than those obtained from LSDV, and the coefficient of the core explanatory variable CR is distinctly improved, but the significance is slightly weaker.

## 6. Conclusions and policy implications

Faced with the severe situations of air pollution control and greenhouse gas emissions reduction domestically and internationally, the collaborative control of air pollutants and greenhouse gas emissions is an important policy choice for China's environmental improvement. This research on synergistic PM<sub>2.5</sub> emissions reduction caused by carbon emissions reduction can provide a quantitative basis for policy makers in the collaborative control of greenhouse gas emissions and air pollution. In this paper, the basic model of Kaya identity is appropriately extended, considering the synergistic effect of CO<sub>2</sub> emissions on PM<sub>2.5</sub> emissions. The variation in PM<sub>2.5</sub> emissions is decomposed by the LMDI decomposition into the synergistic effect of carbon emissions, energy emission intensity effect, energy intensity effect, economic development effect and population effect. Then, this paper analyzes the impacts of five decomposed factors on PM<sub>2.5</sub> emissions changes from national, regional and provincial levels. Based on the LMDI decomposition results, various proxy variables comprising CO<sub>2</sub> emissions reduction, coal consumption rate, technological progress, GDP per capita and its quadratic term, and population density are introduced into the econometric model. By using several rigorous econometric techniques, we further quantify the co-benefits of PM<sub>2.5</sub> emissions reduction generated by CO<sub>2</sub> emissions reduction activities.

The LMDI decomposition method is employed to analyze the influencing factors of PM<sub>2.5</sub> emissions changes from 1998 to 2014. The main conclusions are as follows. (1) From the nationwide decomposition results, the synergistic effect of carbon emissions and energy intensity effect are the main factors resulting in the reduction of PM<sub>2.5</sub> emissions, and the economic development effect is the main reason for the increase of PM<sub>2.5</sub> emissions, while the impacts of population and energy emission intensity are relatively weak. (2) From the perspective of three economic regions, the synergistic effect of carbon emissions and energy intensity effect are conducive to the reduction of PM<sub>2.5</sub> emissions, by contrast, the economic development effect and population effect are the factors leading to the increase of PM<sub>2.5</sub> emissions. In the western region, the energy emission intensity effect leads to the increase of PM<sub>2.5</sub> emissions. However, it has a negative impact on PM<sub>2.5</sub> emissions in the central and eastern regions. From the national perspective,

energy emission intensity changes have a small negative effect on PM<sub>2.5</sub> emissions during 1998–2014. (3) According to the provincial decomposition results, the contribution of each factor differs distinctly in different provinces. For all provinces, the economic development effect is the most important factor resulting in the increase of PM<sub>2.5</sub> emissions. The synergistic effect of carbon emissions and energy intensity effect are the main factors for the decline in PM<sub>2.5</sub> emissions. The population changes make little contribution to PM<sub>2.5</sub> emissions changes. For most provinces, there is large room for the optimization of energy consumption structure. Accordingly, decreasing coal consumption and promoting the use of renewable energy can effectively reduce PM<sub>2.5</sub> emissions for the whole country.

Based on the LMDI decomposition, the impacts of various proxy variables on PM<sub>2.5</sub> emissions reduction are investigated by econometric analysis methods, specially, we focus on the impact of CO<sub>2</sub> emissions reduction on PM<sub>2.5</sub> emissions reduction. The empirical results are complementary to the results of LMDI decomposition. All models indicate that there is a significant synergistic effect of CO<sub>2</sub> emissions reduction on PM<sub>2.5</sub> emissions reduction, and the synergistic effect in the central region is significantly larger than that in the western and eastern regions, indicating that PM<sub>2.5</sub> emissions are more sensitive to CO<sub>2</sub> emissions reduction in the central region. There are large differences in the potential synergistic emissions reduction of PM<sub>2.5</sub> in 30 provinces. Among them, Inner Mongolia, Shanxi, Jiangsu and Shandong have the largest potential synergistic emissions reduction. In addition, it is found that technological progress and population density have positive impacts on PM<sub>2.5</sub> emissions reduction, and there exists a significant inverted U-shaped relationship between economic development and PM<sub>2.5</sub> emissions reduction, while the increase in coal consumption is not conducive to PM<sub>2.5</sub> emissions reduction.

To sum up, this paper proposes the following policy implications. First, regardless of national, regional or provincial level, the synergistic effect of carbon emissions is the main reason for the reduction of PM<sub>2.5</sub> emissions. Therefore, it is necessary to vigorously bring into play the role of the synergistic effect of carbon emissions, which is the most effective way to reduce PM<sub>2.5</sub> emissions. More specifically, coordinating the carbon emissions reduction measures with haze pollution control policies, carrying out the comprehensive and systematic management, thereby reducing the costs of environmental policies. Second, economic development is still the most important factor contributing to haze pollution. As China has started late in PM<sub>2.5</sub> control, haze pollution has not been effectively mitigated with rapid economic development. Specially, there is an inverted U-shaped relationship between economic development and PM<sub>2.5</sub> emissions reduction. Therefore, in the process of economic development, it is necessary to rationally adjust the intensity of environmental regulation, moderately rise the weight of environmental indicator in the index system of local performance evaluation, and coordinate the relationship between economic development and environmental protection. Third, given China's resource endowment, energy mix has relatively little impact on PM<sub>2.5</sub> emissions than other factors. The potential contribution of energy mix optimization to PM<sub>2.5</sub> emissions reduction cannot be ignored in most provinces. More importantly, it is necessary to improve the efficiency of energy processing conversion and utilization in CO<sub>2</sub> emissions reduction activities, such as developing clean coal technology and promoting new energy power generation. Fourth, technological progress is conducive to the reduction of PM<sub>2.5</sub> emissions, but technological progress may cause an increase in PM<sub>2.5</sub> emissions through CO<sub>2</sub> emissions reduction activities, i.e., synergistic emissions increase. Accordingly, it is required to discriminatively develop the haze pollution mitigation technology and low-carbon energy saving technology,

strengthen the investment in the research and development of pollution control technology, and adopt more direct end-of-pipe treatment measures against haze pollution. Fifth, the development of compact cities and population agglomeration are conducive to promoting the intensive energy utilization, reducing the energy waste and improving the heating efficiency, thereby contributing to alleviating haze pollution.

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